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A conceptual model for determining an optimal drug testing policy was developed which compared drug use in the Navy with a demographically equivalent group of civilians. A new measure of drug use, a drug-day, was defined as a day on which the user could test positive if subjected to drug testing. Algorithms were presented which estimate the deterrence and detection effects of alternative drug testing rates. The cost per drug-day was determined based on the estimated relationship between substance abuse and employee productivity in the civilian sector. Estimated benefits were compared to the cost of drug testing in order to assess the net benefit of drug testing and determine optimal test rates. Preliminary estimates derived from the conceptual model indicated that present levels of Navy drug testing were cost beneficial. Annual net benefits were estimated to exceed $23 million.

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Foreword

This report was prepared as part of the In-House Independent Laboratory Research Program task (Program Element 0601152N, Project R0001, Work Unit 0601152N.R0001.17) *A Conceptual Model for Determining an Optimal Drug Testing Program* sponsored by the Office of Naval Research. The objective of this task is to develop a conceptual framework for determining an appropriate random urinalysis drug testing program. This effort provides a framework which extends and integrates methodologies for measuring detection and deterrence developed as part of the Statistical Methods for Drug Testing project (Program Element 0305889N, Work Unit 0305889N.R2143DR001) sponsored by the Chief of Naval Personnel (PERS-63).

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Summary

Background

The Navy's zero tolerance drug policy began in 1981. Since then the Navy has pursued an aggressive urinalysis testing program. The program is intended to deter and detect drug abuse. All officer and enlisted personnel are subject to random urinalysis testing on a continuing basis. Current policy (Chief of Naval Operations, 1994) directs Navy Commands to test 10 to 30 percent of their members each month. The program has been considered successful; the proportion of service members testing positive for drugs has fallen from approximately 7 percent in 1983 to less than 1 percent in recent years. The annual cost of the testing program is approximately $20 million. The cost of drug testing is high but any drug abuse impacts readiness, health, and safety. Therefore, it is of importance that the Navy continue to evaluate and improve its drug testing program and seek to develop an optimal drug testing strategy.

Previous drug-related research has yielded models for estimating the probability of detecting drug abusers with specific patterns of drug usage. The Navy Personnel Research and Development Center (Thompson & Boyle, 1994b; Boyle, Hentschel & Thompson, 1993; Thompson, Boyle & Hentschel, 1993) and the Center for Naval Analysis (Evanovich, 1985) have developed a series of models based upon Markov chains which estimate both the probability of detection and the expected duration until detection of a class of drug abusers. Models have been extended to include certain aspects of drug wear-off (Thompson & Boyle, 1994a).

While these models are helpful in analyzing the relationships between random drug-testing policies and the probability of detection within specified periods of time, they were not formulated within the context of an underlying rationale or conceptual model which incorporates key aspects of drug testing and the relationships among them. The concepts of deterrence, detection, gaming and non-gaming users, and the components of costs and benefits have not been rigorously defined and the relationships between these components has not been postulated. Without an underlying conceptual model, the ability to determine an optimal drug testing policy is sharply diminished and selection of specific testing rates and strategies must be based on general impressions rather than scientific models.

Objective

The objective of this effort was to develop a conceptual model for determining an optimal drug testing strategy. Such a model includes the objectives of a drug testing program and approaches for defining costs and benefits. Detection and deterrence, selection of relevant probabilistic models, and potential gaming by personnel were to be considered and incorporated into model conceptualization.

Methodology

A conceptual model for determining an optimal drug testing policy was developed which compared drug use in the Navy with a demographically equivalent group of civilians. Various measures of drug use, such as the proportion of individuals using drugs within a 30-day period, frequency of drug use, and the types of drug being used were discussed. A new measure of drug

use, a "drug-day," was defined as a day on which the user could test positive if subjected to drug testing. Conceptually, drug testing deters some individuals from using drugs (or diminishes the frequency of use) which decreases the number of drug-days accumulated by the Navy. Each drug-day imposes a cost on the Navy in terms of lower productivity and potentially higher health costs and accident rates. Algorithms were developed which estimate the deterrence effect of alternative drug testing rates. Individuals whose drug use has not been fully deterred run the risk of detection; algorithms to estimate these detection effects for alternative drug testing rates are also discussed. The drug-days remaining after deterrence and detection can be compared to initial estimates of Navy drug use which assume that no drug testing is performed. Estimates of the cost per drug-day were based on relationships between substance abuse and employee productivity in the civilian sector. This cost metric was applied to the reduction in drug-days resulting from drug testing in order to determine the benefit of testing at specific monthly test rates. Estimated benefits were compared to the cost of drug testing in order to assess the net benefit of drug testing and determine optimal test rates.

Results

The conceptual model linked the concepts of deterrence, detection, costs, benefits, net benefits, and optimal testing strategies. Preliminary estimates derived from the conceptual model indicated that present levels of testing (approximately 20%) are cost beneficial. Testing at present levels was conservatively estimated to yield an annual benefit of $260.7 million compared to annual costs of approximately $237.7 million.

Conclusions and Recommendations

The development of an automated model based upon this conceptual approach appears to be feasible. It is recommended that the conceptual model form the basis of a computerized drug policy analysis system for use by drug policy managers to determine optimal drug testing strategies. It is further recommended that additional parameters such as differential testing for specific drugs (i.e., pulsing) and a wider variety of drug testing strategies (e.g., testing based on anticipated likelihood of drug use) be incorporated into the model.

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Introduction

The Navy's zero tolerance drug policy has been in effect since 1981. Since then the Navy has pursued an aggressive urinalysis testing program. The objectives of this testing program have been to deter and detect drug abuse, as well as provide data on the prevalence of drug abuse. All uniformed personnel are subject to random urinalysis testing on a continuing basis. Current policy (Chief of Naval Operations, 1994) directs Navy commands to test 10-30 percent of their members each month. The program has been considered successful; the proportion of sampled service members testing positive for drugs has fallen from approximately 7 percent in 1983 to less than 1 percent in recent years. The annual cost of the testing program is approximately $20 million. Because of the effects of drug abuse on readiness, health, and safety, it is important that the Navy continue to evaluate and improve its drug testing program and seek to develop an optimal drug testing strategy.

Previous drug-related research has developed models for estimating the probability of detecting drug abusers with specific patterns of drug usage. A series of models based upon Markov chains have been developed which estimate both the probability of detection and the expected duration until detection of a class of drug abusers (Thompson & Boyle, 1994b; Boyle, Hentschel, &Thompson, 1993; Thompson, Boyle, & Hentschel, 1993; Evanovich, 1985). Models also have been extended to include certain aspects of drug kinetics (Thompson & Boyle, 1994a).

While these models are helpful in analyzing the relationships between random drug testing procedures and the probability of detection within specified periods of time, they fail to evaluate the economic efficiency of alternative drug testing policies. In particular, no attempt has been made to evaluate the economic benefits of drug testing. Furthermore, a key element of the program that generates significant benefits--the deterrence effect--has been ignored. As a result, the ability to determine an optimal drug testing policy is sharply diminished and selection of specific testing rates and strategies must be based on general impressions rather than scientific evidence.

Objective

The objective of this research is to develop a conceptual model for determining an optimal drug testing strategy. Model development includes selection of an appropriate objective for a drug testing program and development of alternative approaches for defining and measuring economic costs and benefits. Such issues as detection and deterrence, selection of relevant probabilistic models, and potential gaming by personnel are considered. Developing, refining, and linking concepts such as program costs, program benefits, probability of detection, deterrence, and drug kinetics is a principal objective of this effort.

The report is organized as follows. The methodology section is divided into four subsections. The first subsection introduces conceptual measures of the cost of drug abuse. This concept is then used to identify the deterrence effect associated with the drug testing program. In addition, this section discusses the probability of detecting drug users and develops an overall conceptual model. The model provides links between the civilian sector, the Navy, and the drug testing program. The second subsection derives the principles of economic optimization which provide the framework for a cost-benefit analysis of the testing program. The third subsection estimates the deterrence effect of the drug testing program and the last subsection estimates the detection effect. The results

section uses these estimates to calculate the program costs and benefits, and the final section provides conclusions and recommendations.

Methodology

Conceptual Model

In order to develop a conceptual model for determining an optimal drug testing program, it is necessary to rigorously define the cost of drug abuse to the Navy. The benefits of deterrence and detection lie in avoiding these costs. In order to define the cost of drug abuse, we introduce the concept of Navy drug-days.

Navy Drug-Days

The concept of Navy drug-days is based on Navy policy which states that drug abuse is incompatible with Naval Service. As a consequence of this policy, any day on which a Navy member could test positive for illegal drug use if selected for testing imposes an economic cost in terms of lost productivity, absenteeism, increased medical costs, greater likelihood of accidents or crime, etc. The objective of Navy drug policy is to minimize and, hopefully, eliminate illegal drug use. If α_{ij} represents the conditional probability that the *ith* individual would test positive if subjected to drug testing on day *j*, it follows that an objective of Navy policy is to minimize $\sum_i \sum_j a_{ij}$. For any period, a drug-day d_{ij} can be defined as any day during a period when $\alpha_{ij} > 0$. Two alternative techniques can be used to measure drug-days during a given period.

Definition 1: $d_{ij} = 1$ if $\alpha_{ij} > 0$; otherwise $d_{ij} = 0$.

This definition counts a day as a drug-day when the individual exhibits a positive probability of testing positive. The magnitude of the probability does not impact the value. Thus, if a given facility counted 10 drug-days during a month, this would imply that the potential for 10 positive drug tests existed during this period. We assume that an individual is not tested more than once on any given day.

Definition 2: $d_{ij} = \alpha_{ij}$.

An alternative definition uses the magnitude of the probability of testing positive as the metric for quantifying drug-days. For example, a person with a probability of .10 of testing positive on each day during a 30-day testing month would contribute three drug-days to the overall total. Under Definition 1, this person's contribution would have been 30 drug-days. Under Definition 2, $\sum_i \mathrm{d}_{ij}$ represents the expected proportion of all Navy members who would test positive on a given day.

It is a policy decision as to which metric is the better measure of drug abuse in the Navy. However, using the second definition, the number of drug-days is (under certain randomness

assumptions) directly estimable from available Navy drug test data as the observed proportion of examinees who test positive.[1]

Cost of Drug Abuse

If c_{ij} represents the cost to the Navy (the cost to the individual can be included in this value) of the *ith* individual under the influence of drugs on the *jth* day during a period, the total cost of drug abuse can be measured as $\sum_i \sum_j c_{ij} d_{ij}$. If the cost of drug abuse is the same on all days, but varies for specific demographic groups (g), (e.g., officers vs. enlisted), the total cost becomes $\sum_g c_g \sum_{i,j \in g} d_{ij}$. Therefore, the cost of drug abuse can be estimated once a suitable value for c_g has been determined. The benefits of drug testing at level p, B^0_p, where p is the test rate during a period (e.g., a month) can be best estimated as:

$$B^p_0 = \sum_g c_g \sum_{i,j \in g} d^0_{ij} - \sum_g c_g \sum_{i,j \in g} d^p_{ij} \tag{1}$$

where d^p_{ij} represents the occurrence of a drug-day when the test rate is p and d^0_{ij} represents the occurrence of a drug-day when no testing is conducted during the period. The benefits of drug testing are based on the costs avoided, which are produced via a deterrence and a detection effect.

Deterrence Effect

Let α^p_j represent the proportion of individuals in the Navy who would test positive for drugs on day j when the test rate (e.g., monthly) is p. Similarly, let $\alpha^{p'}_j$ represent the analogous proportion for test rate p′. The deterrence effect of test rate p′ relative to p, $D^{p'}_p$ is defined as $\alpha^p_j - \alpha^{p'}_j$. Thus, if the proportion who test positive under policy p and p′ are .05 and .02, respectively, then $D^{p'}_p = .03$. In this example, there is a 60 percent reduction in the number of positives.

Deterrence effects can be transformed into Navy drug-days in the following manner. Let INV_j represent the personnel inventory on day j. Using Navy drug-day definition 2, it follows that $\sum_i d^p_{ij} = \left(\alpha^p_j\right)(INV_j)$. Therefore,

$$D^{p'}_p\,(INV_j) = \sum_i d^p_{ij} - \sum_i d^{p'}_{ij} \tag{2}$$

---

[1]Using either metric, it is the goal of current Navy policy to minimize $\sum_i \sum_j d_{ij}$. We are taking this policy as a given, even though it could also be questioned on efficiency grounds.

We shall assume that deterrence effects do not vary by day, j, or demographic group, g. Let $BD_p^{p'}$ represent the benefit due to deterrence of testing rate p' relative to p. It follows from (1) and (2) that:

$$BD_p^{p'} = D_p^{p'} \sum_g c_g \sum_j INV_{gj} \tag{3}$$

where INV_{gj} represents the inventory of group g on day j. The test rate may vary over time periods, but other aspects of test policy may be assumed to be time-invariant or inconsequential.

Detection Effect

The detection effect of a drug testing strategy can be measured by its probability of detecting drug users with specific patterns of drug usage. Stoloff (1985) notes that many variables affect the probability of detection including patterns of drug use, frequency of drug use, potency of the drug, and the sensitivity level of the test. Drug users may also be gaming or non-gaming, that is, they may or may not vary their drug intake depending upon their perceived probability of detection. Borack (1996a; 1996b) provides a methodology for estimating the probability of detecting both gaming and non-gaming users. In particular, the probability of detecting a non-gaming user during a month with monthly test rate p, is shown to be:

$$(DET_p) = p \sum_{i=1}^{w} \alpha_i \frac{\binom{M-i}{k-1}}{\binom{M}{k}} \tag{4}$$

where p = monthly test rate, α_i is the probability of testing positive i days after drug usage, M is the total number of days in the period (e.g., a month), W is the length of time (in days) the drug remains detectable (i.e., wear-off period), and k is the number of days the individual uses drugs during the period. The values of α_i are based on drug kinetics as discussed in Thompson and Boyle (1994a) and are assumed to be non-cumulative. Other formulas based upon alternative assumptions are also presented in Borack (1996a).

Borack (1996b) develops an algorithm for determining an optimal strategy for a gaming drug user. The algorithm assumes that the user will choose his next day of drug use so as to minimize the probability of detection. For example, if a drug is detectable for one day and no testing is conducted on Sunday and Monday, the user will prefer to use drugs on Sunday, or on Saturday after normal testing time. For a specific monthly test rate, p, and test strategy, use of these algorithms permits estimation of the probability of detecting a gaming drug user during the month as well as the expected time until detection. In general, the expected number of months until detection, $E(DET_p)$ can be calculated from the geometric distribution (Feller, 1957):

$$E(DET_p) = \frac{1 - P(DET_p)}{P(DET_p)} + .5 \tag{5}$$

assuming that detection occurs at the mid-point of the month. Therefore, the detection effect on the *ith* user of drug testing strategy p relative to p', $DET_{ip}^{p'}$, an be estimated as the difference in the expected number of drug-days until detection:

$$DET_{ip}^{p'} = [E(DET_{ip'}) - E(DET_{ip})] \sum_j d_{ij}^p \qquad (6)$$

where $\sum_j d_{ij}^p$ represents the number of drug-days accumulated by the *ith* user during a period (e.g., month). This can also be viewed as either the number of additional days until detection multiplied by the average conditional probability of detection during the month or as the number of additional missed opportunities to detect users.

From (6), assuming consistent patterns of drug use across months and summing over all types of users, it follows that:

$$BDET_p^0 = \sum_g c_g \sum_{i, i \in g} (E(DET_{i0}) - E(DET_{ip}))\ d_{ij}^p \qquad (7)$$

Since $E(DET_{i0}) = \infty$, to determine the annual benefit of detection, $E(DET_{i0})$ equals the number of days within the observation period + 1, e.g. 366 days. That is, the entire period will pass until detection occurs. The concepts of cost, deterrence and detection will now be integrated into a conceptual model for determining an optimal drug testing program.

Conceptual Model

Figure 1 describes a conceptual model for determining an optimal drug testing policy.

Navy personnel are recruited from the civilian sector and can be segmented by age, sex, race, geographic location, socio-economic status, and other factors related to the likelihood of using illegal drugs. These factors determine the propensity for drug use, or equivalently, yield an expected proportion of drug users. Let p_h represent the probability that a civilian with specific attributes would use drugs during the period. Then, $\hat{p}_g = \sum_h p_h p_{gh}$ represents an estimate of the proportion of civilians with attributes similar to those in Navy subgroup g who would use drugs during the period. Here, p_{gh} represents the proportion of individuals in Navy group g who are also in attribute group h (e.g., young, male, enlisted). It follows that $\sum_g \hat{p}_g INV_g$ represents the expected number of individuals using drugs during the period. This inventory can be viewed as an adjusted civilian inventory based on relevant attributes of Navy personnel. Let $\hat{d}_{g,p} = \sum_{i,j \in g} \hat{d}_{ij}^p = f\left(\sum_g p_g INV_g\right)$ represent a function which transforms the expected number of individuals using drugs during a period with test rate p into an estimate of the corresponding

number of drug days. Then, $\hat{c}_0 = \sum_g c_g \sum_{i,j \in g} \hat{d}_{ij}^{0}$ represents the estimated expected cost of drug abuse to the Navy in the absence of drug testing. These figures can similarly be viewed as an adjustment to civilian sector data based on relevant attributes of Navy personnel. The deterrence and detection effects of testing alter the inventory of drug users and correspondingly lead to a revised cost of drug abuse to the Navy. The overall estimated benefit of drug testing at level p is then

$$\hat{B}_p^{0} = \sum_g c_g \sum_{i,j \in g} \left(\hat{d}_{ij}^{0} - \hat{d}_{ij}^{p} \right) \tag{8}$$

which includes both deterrence and detection effects. Equation (8) assumes that entry into the Navy does not alter the propensity to use drugs. It also bases the implied cost of drugs to the Navy on the assumption that no other effective drug demand reduction strategies are undertaken.

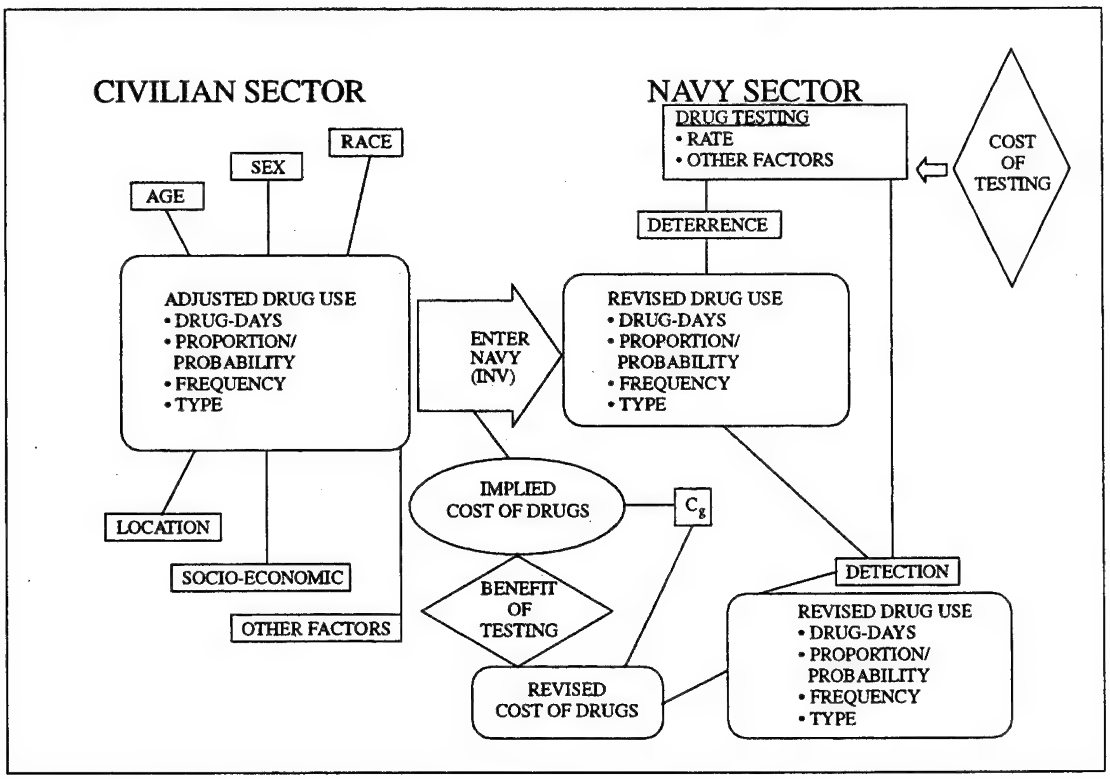

Figure 1. Conceptual model for determining an optimal drug detection program.

As noted above, the Navy's testing program results in a deterrence effect which is manifested through changes in the proportion of the inventory using drugs, the frequency and types of drugs being used, and the resulting decrease in the number of drug-days. This results in a new, lower implicit cost of drugs due to the deterrence effect. Finally, this revised inventory is subject to detection and the number of drug-days is further reduced as a result of the dismissal of those who test positive. Note that detected personnel must be replaced. It is assumed the post-detection drug

use profile represents a per-capita pattern and must be inflated to the initial inventory in order to estimate the revised cost of drugs based upon required inventory. The difference between the initial implied cost of drugs and the revised cost of drugs represents the benefit of testing.[2] This formulation implicitly attributes the reduction in the cost of drugs almost entirely to drug testing.

Evidence from the 1992 Worldwide Survey of Substance Abuse and Health Behaviors Among Military Personnel (1992 WWS) (Bray et. al., 1992) supports this assumption. The WWS found that 9.8 percent of the civilian sector (demographically adjusted to the 1992 DoD personnel inventory) indicated they had used drugs during the past 30 days. Using comparable DoD ratios, this is equivalent to approximately 17.8 percent of military personnel using drugs during the past 12 months. Since 6.6 percent of Navy personnel stated that they used drugs during the past 12 months, we can estimate a deterrence effect of approximately 11 percentage points (or 63 percent relative to civilian drug use).

The survey also asked whether individuals would be more likely to use drugs in the absence of testing. Approximately 10.5 percent of non-users responded they would be more likely to use drugs in the absence of testing. Since 93.4 percent of Navy personnel did not indicate drug use during the past 12 months, we estimate that approximately (10.5)(93.4) = 9.8 percent additional personnel would use drugs in the absence of testing. This is consistent with the initial estimate of deterrence above. Also note that 82.2 percent of non-users stated that they would not use drugs even if there were no drug testing. Thus, 17.8 percent of the non-users, or (17.8)(93.4) = 16.6 percent of the Navy, would face an increased risk of drug use. Since 6.6 percent of Navy respondents stated they had used drugs during the past 12 months, the absence of drug testing could potentially increase drug use to more than 23 percent of the inventory. This further reinforces the argument that drug testing is the primary deterrent to drug use in the Navy. Additional support comes from comparing military and civilian drug use in 1980, before implementation of Navy drug testing with the zero tolerance policy (Burt, Biegel, Carnes, & Farley, 1980). Table 1 reproduces these data which were standardized with respect to sex, age, marital status, and education. As is evident from the data at that time, there was little difference in overall drug use between the military and civilian populations.

An alternative, simpler model formulation considers drug use within the context of a flow model.

Figure 2 illustrates the reduction in the proportion of drug users resulting from a given level and process of drug testing. From Figure 2, the reduction is equal to $p - p(1-p')(1-p'') = p(p' + p'' - p'p'')$ where p is the proportion using drugs in the absence of testing, p' is the proportion deterred by drug testing, and p'' is the proportion detected by drug testing. The magnitudes of p' and p'' are functions of the level and type of drug testing. Functions will be derived in later sections to estimate the reduction in drug-days as a function of the change in the proportion of drug users.

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[2] The estimation of benefits as the difference between the initial implied cost of drugs and the final adjusted cost of drugs assumes that the cost of a drug user undetected during the entire period is at least as great as the cost of a detected drug user, despite the fact that the drug user must be replaced. Therefore, the estimation of c_g must include this assumption as a lower boundary condition.

Table 1

Prevalence of Nonmedical Drug Use and Alcohol Use During 1980 Among Military Personnel and Comparable Civilians--Ages 18-25 (Percentage of 18-25 Year Old Population)

Type	Military	Comparable Civilians
Marijuana/Hashish		
Past 30 Days	40	42
Past 12 Months	52	54
Amphetamines		
Past 30 Days	10	4
Past 12 Months	21	12
Cocaine		
Past 30 Days	7	10
Past 12 Months	18	23
Hallucinogens		
Past 30 Days	5	5
Past 12 Months	13	12
Barbiturates		
Past 30 Days	4	4
Past 12 Months	9	10
Tranquilizers		
Past 30 Days	3	3
Past 12 Months	9	12
Heroin		
Past 30 Days	1	1
Past 12 Months	3	3

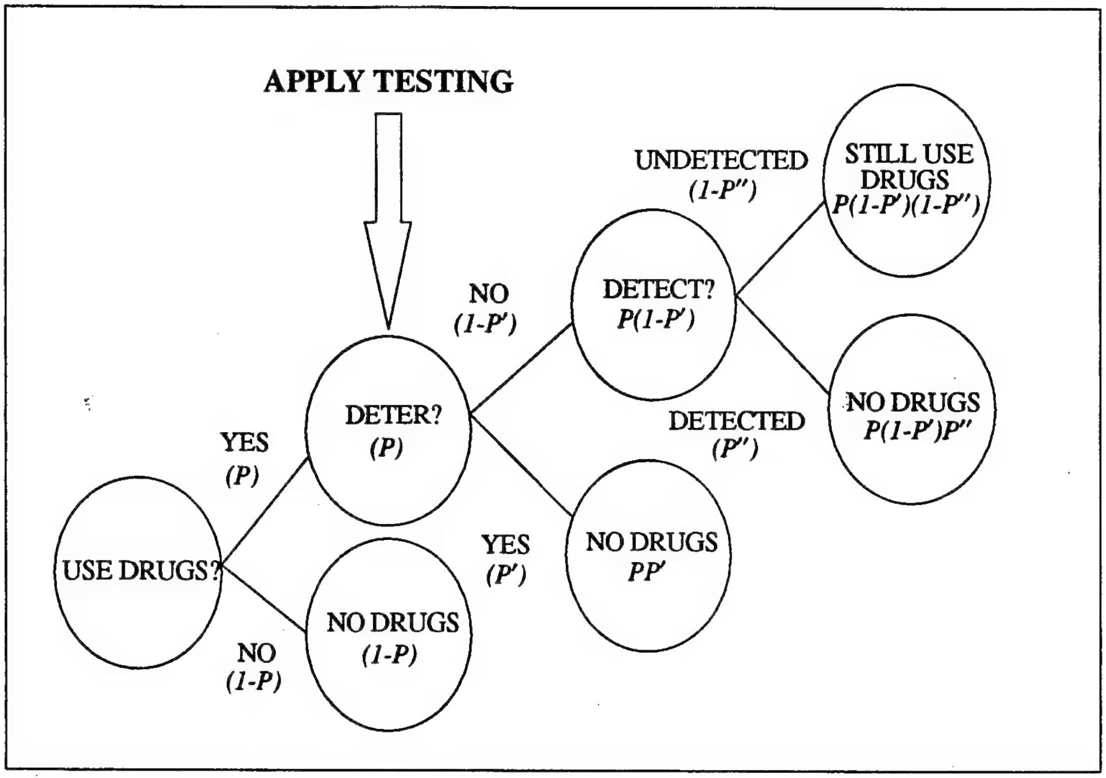

Figure 2. Alternative depiction of conceptual model.

Optimization

The goal of the conceptual model is to establish the optimum size of the drug testing program. The equilibrium conditions for an economic (efficient) optimum can be easily derived. Suppose that the testing program is viewed as producing output, where the output might be, say, accidents avoided. For the moment, we can further assume that the value of each unit of output is weighted equally. Let the output be produced via the following production function:

$$f(x) = f[(1-\gamma)L] = Q \tag{9}$$

where, L = stock of labor

γ = proportion of labor force using drugs, where γ is a function of the test rate, p

$(1-\gamma)$ = proportion of labor force not on drugs.

The total cost of testing is simply a function of the testing rate, p:

$$TC = TC(p) \tag{10}$$

We assume diminishing returns in the output function, $f' > 0, f'' < 0$ and $\gamma < 0, \gamma' > 0$. Consequently, the marginal cost is rising, $TC' > 0$.

Optimization requires simply maximizing net benefits, or the difference between (9) and (10), with respect to p. The first-order condition is:

$$- L \gamma f' - TC' = 0$$

or,

$$-[L\gamma f'] = MC \qquad (11)$$

where MC = marginal cost. One part of the LHS, $(-L)f'$, represents additional lost output for a given increase in the proportion of the labor stock using drugs. The product $(\gamma)(-Lf')$, represents the gain in output from increasing the testing rate. Since $(\gamma) < 0$ and $-Lf' < 0$, the product is positive.

This condition duplicates the standard equilibrium condition for maximizing net benefits. It simply states that, at the optimum the marginal benefit from increasing the test rate should equal the marginal cost. As Figure 3 shows, at the point where $MB = MC$, net benefits are maximized. The remaining sections attempt to quantify the benefits and costs of the program, where benefits are based on its deterrence and detection effects.

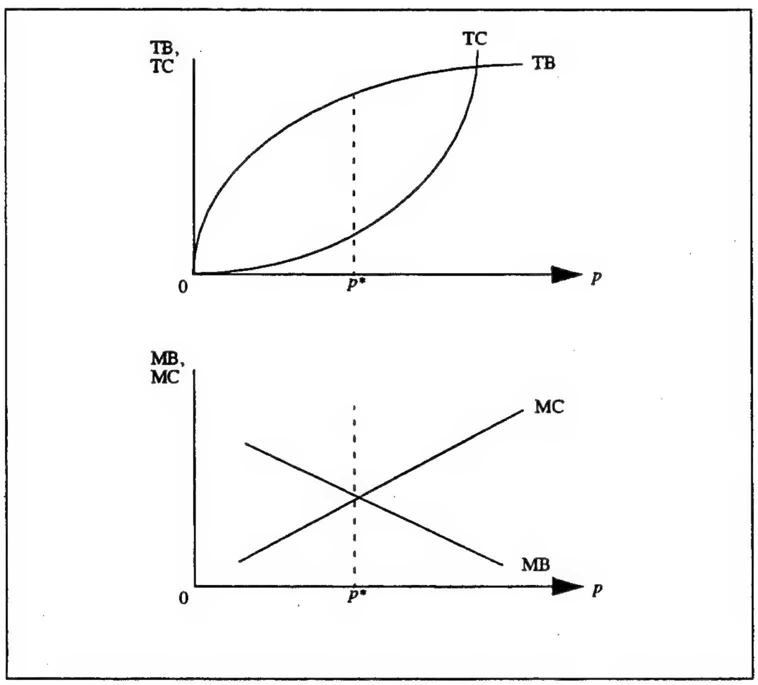

Figure 3. Costs and benefits of alternative testing rates.

Estimation of the Deterrence Effect

The deterrence effect $\alpha_j^p - \alpha_j^{p'}$ measures the impact of the test rate on drug use and the subsequent conditional probability of testing positive. If higher test levels produce increased deterrence, then increased test rates would tend to be associated with lower reported drug usage relative to an equivalent civilian population.

In order to estimate the baseline drug use rate, α_j^0. it is necessary to estimate the proportion and frequency of drug use in the absence of testing. As noted previously, it is first necessary to estimate the expected number of individuals using drugs during the period if no testing were conducted, $N_{30,0} = \sum_g p_g INV_g$. Table 2 presents data from the 1991 National Household Survey on Drug Abuse on the prevalence of illicit drug use among civilian personnel during the past 30 days. Estimates were standardized to military data by age, education, race/ethnicity, and marital status (Bray, et al., 1992). Applying these proportions to the 1994 Navy inventory, disaggregated by age and gender, yields estimates of p_g for enlisted and officer personnel. These proportions are presented in Table 3. The table also presents the estimated value of $N_{30,0}$. We estimate that approximately 9.96 percent of Navy personnel would use illicit drugs at least once during a 30-day period if there were no drug testing.

Table 2

Standardized Estimates of the Prevalence of Any Illicit Drug Use Among Civilians, Past 30 Days, for Persons Ages 18-55

Sex/Age Group	Percentage Using Drugs
Males	
18-25	15.4
26-55	6.9
All Ages	10.1
Females	
18-25	12.2
26-55	4.8
All Ages	8.3
Total	
18-25	14.8
26-55	6.7
All Ages	9.8

Source. Table 5.8 appearing in Bray, et al., (1992).

Table 3

Estimated Proportion ($p_{30,0}$) and Number ($N_{30,0}$) of Navy Personnel Who Would Use Any Illicit Drug During a 30-Day Period if There Were no Drug Testing

Military Status	p_g	INV_g	p_gINV_g
Enlisted	.1035	426,542	44,144
Officer	.0736	63,750	4,692
Overall	$p_{30,0} = .0996$	490,292	$N_{30,0} = 48,836$

In order to estimate the deterrence effect of a specific drug test rate, estimates of $p_{30,0}$ were constructed for 1980, 1982, 1985, 1988, and 1992. The estimates for 1985, 1988, and 1992 were developed using the methodology described above based upon corresponding data from civilian surveys for the same years (Bray, et al., 1986; 1989; 1992). Demographically comparable data were not available for 1980 and 1982, so rough estimates were obtained by first estimating the proportion of users of any drug from data available for specific drugs (see Table 1). Using these proportions for 18-25-year-old males, estimates for the remaining demographic groups were obtained under the assumption that the ratios of drug use of 18- to 25-year-old males to that of the other groups in 1980 and 1982 were the same as for the 1985 sample. These rates were then applied to corresponding annual inventories to obtain $p_{30,0}$.

Estimates of $p_{30,p}$ were obtained directly from the corresponding year WWS, and are presented in Table 4. The column headed r represents the ratio of the number of laboratory tests to the corresponding annual inventory; the column headed p represents the corresponding average proportion tested during a month (monthly test rate).

Table 4

Estimates of $p_{30,0}$ and $p_{30,p}$ for Fiscal Years 80, 82, 85, 88, and 92

Fiscal Year	$p_{30,0}$	$p_{30,p}$	r	p
80	.363	.330	0.000	0.000
82	.270	.162	0.725	0.060
85	.244	.103	2.442	0.204
88	.150	.054	2.562	0.214
92	.105	.040	2.518	0.210

In order to estimate the relationship between the underlying test rate, p, and the deterrence effect, a logarithmic regression model was fit to the percentage difference between $p_{30,0}$ and $p_{30,p}$ (*PDIFF*) as a function of the logarithm of p, yielding the following parameter estimates:

$$PDIFF(p) = .8675 + .1699 \ln(p) \tag{12}$$

The value of p was scaled upward by one unit to avoid zero values. The corresponding values of adjusted R^2 and F were .987 and 314.59, respectively which are both highly significant. Figure 4 graphically depicts this relationship. The actual data are also presented. This model implies that if 100 percent testing were implemented, the achievable reduction in drug use would be approximately 86.9 percent.

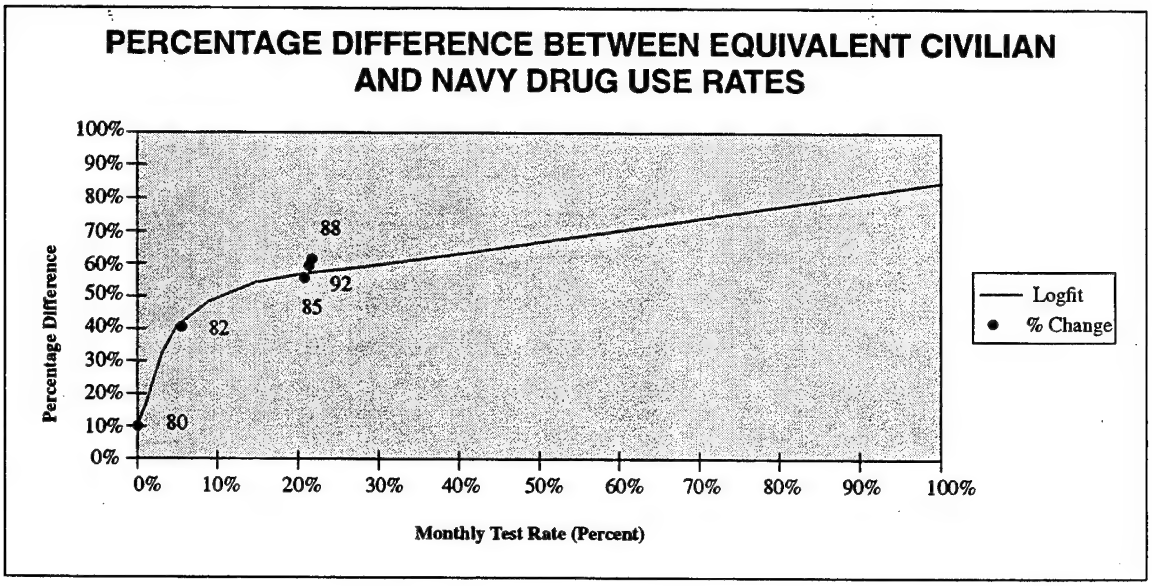

Figure 4. Percentage difference between equivalent civilian and Navy 30-day drug use rates.

Finally, in order to determine the deterrence effect of a given monthly test rate, we estimate the relationship between the number (or proportion) of drug users within a 30-day period and the corresponding number of drug-days. Let $\hat{d}_{g,p} = \sum_{i,j \in g} \hat{d}_{ij}^{p} = f(N_{30,p})$ represent a function which estimates the number of drug-days from the number of drug users. In order to estimate this function, Table 5 presents data from the 1992 WWS which tabulates the frequency of use of any drug during the past 30 days. Note that similar profiles for specific drugs can be developed from data appearing in Tables 7 and 8 of the following section, which discusses estimation of the detection effect. Table 5 is based upon data from Table 8. The first row of Table 5 includes all individuals while the second row includes only users. The last row applies these proportions to the estimate of $N_{30,0}$ in Table 3. This procedure assumes the frequency of drug use is independent of group, g. In general, if f_k represents the proportion of users who use drugs k days during the period (here, 30 days), then:

$$\hat{d}_{g,p} = N_{30,p} \sum_k \hat{d}_{w,k} f_k \tag{13}$$

where $\hat{d}_{w,k}$ represents the estimated number of drug-days per user as a function of w and k. Borack (1996a; 1996b) provides a methodology for estimating $E(\alpha)$, the expected conditional probability of testing positive (if selected for testing) as a function of w and k. The expected number of drug-days per month per user can therefore be estimated as:

$$\hat{d}_{w,k} = 30 \;\; E(\alpha) \tag{14}$$

where 30 represents the number of days in a typical month. Assuming the proportion of gaming users to equal those of any drug found in Table 8, Table A.1 in the appendix provides values of $\hat{d}_{w,k}$ for $w = 2$ for gaming and non-gaming users. Therefore, assuming a 2-day wear-off period, approximately 362,851 drug-days (i.e., 7.43 days/user) would be accrued during a 30-day period based upon the 1994 Navy inventory. Therefore, on an average day, 362,851/30 or 12,095 individuals representing 12,095/490,292, or 2.47 percent of the Navy could test positive if there were no drug testing program. Assuming that frequency and type of drug among users is unaffected by monthly test rate, the percentage decrease from this rate can be obtained from (12). For example, the daily deterrence effect of testing at a 100 percent monthly rate would be estimated as approximately 2.47(.869) = 2.15 percent.

Table 5

Frequency of Drug Use Among Navy Personnel

	Frequency (Days in Use)					
	Never	1-3	4-10	11-19	20-27	28-30
% Overall	90.04	6.18	2.19	1.18	.25	.15
% Users		62.06	21.99	11.87	2.48	1.60
# of Users		30,308	10,739	5,797	1,211	781

Source. Worldwide Survey of Substance Abuse and Health Behaviors Among Military Personnel, 1992.

Estimation of the Detection Effect

From (6), it is clear that the detection effect of a drug testing policy depends on the underlying pattern of drug use. In order to estimate the underlying pattern of drug use, data from the 1992 WWS were analyzed. Table 6 presents the stated frequency of drug use of specific drugs by Navy personnel within the past 30 days.

During this period, marijuana was the most commonly used drug followed by analgesics, LSD, cocaine, inhalants, and designer drugs. No other drug was used by more than 0.23 percent of the Navy.

Table 6

Drug Use by Navy Personnel During Past 30 Days (in percent)

	Frequency (Days in Use)					
Drug	Never	1-3	4-10	11-19	20-27	28-30
Marijuana	98.22	1.29	0.18	0.22	0.08	0.00
PCP	99.93	0.07	0.00	0.00	0.00	0.00
LSD	98.69	0.82	0.49	0.00	0.00	0.00
Cocaine	98.95	1.03	0.02	0.00	0.00	0.00
Amphetamines	99.78	0.16	0.07	0.00	0.00	0.00
Tranquilizers	99.77	0.07	0.01	0.13	0.00	0.01
Barbiturates	99.84	0.07	0.08	0.01	0.00	0.01
Heroin	99.93	0.07	0.00	0.00	0.00	0.00
Analgesics	98.65	0.98	0.16	0.16	0.00	0.05
Inhalants	99.28	0.53	0.11	0.08	0.00	0.01
Designers	99.53	0.38	0.08	0.00	0.00	0.00
Steroids	99.93	0.00	0.07	0.00	0.00	0.00
Any Drug	**96.00**	**1.81**	**0.87**	**1.09**	**0.07**	**0.17**

Source. Worldwide Survey of Substance Abuse and Health Behaviors Among Military Personnel, 1992.

The detection effect of a test program is also affected by gaming strategy. The 1992 WWS asked personnel whether they agreed with the statement: "Some drug users curtail use when they think they'll be selected for urinalysis." Results indicated that 59.6 percent of self-reported Navy drug users either agreed or strongly agreed with this statement. Responses to this question were cross-tabulated with frequency of drug use. Individuals who used more than one drug were categorized by the drug used most frequently. In cases where two or more drugs were used with the same frequency, the individual was categorized by the drug used most infrequently within the Navy. Thus, if an individual used marijuana and PCP for 1-3 days, the individual was characterized as a PCP user for 1-3 days. This technique results in the proportion of users with a specific frequency of use of any drug to equal the sum of the proportions with that frequency of use of specific drugs. Table 7 presents these results.

Table 7 can be modified to include only marijuana, LSD, analgesics, cocaine, inhalants, and designer drugs because the remaining drugs are rarely used or not tested. (For a more detailed explanation, see footnote 3.) Table 8 presents the results of this modification.

Table 7

Percentage of Navy Drug Users by Drug, Frequency of Use, and Gaming Strategy During the Past 30 Days

	Frequency of Use (Days during Month)									
	Gaming User					Non-Gaming User				
	1-3	4-10	11-19	20-27	28-30	1-3	4-10	11-19	20-27	28-30
Marijuana	14.77	1.28	1.96	2.14	0.00	1.16	0.00	2.77	0.00	0.00
PCP	1.66	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00
LSD	4.12	12.37	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00
Cocaine	11.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Amphetamines	0.34	1.66	0.00	0.00	0.00	1.67	0.00	0.00	0.00	0.00
Tranquilizers	0.40	0.13	0.33	0.00	0.00	0.86	0.19	2.77	0.00	0.00
Barbiturates	0.00	1.85	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.30
Heroin	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Analgesics	3.80	3.71	1.03	0.00	0.00	16.77	0.00	2.84	0.00	1.31
Inhalants	1.96	0.00	0.00	0.06	0.00	0.54	1.03	1.96	0.00	0.15
Designers	0.00	0.00	0.00	0.00	0.00	0.30	0.00	0.00	0.00	0.00
Steroids	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Any Drug	**38.05**	**21.00**	**3.57**	**2.26**	**0.00**	**21.79**	**1.23**	**10.35**	**0.00**	**1.75**

Source. Worldwide Survey of Substance Abuse and Health Behaviors Among Military Personnel, 1992.

Table 8

Percentage of Navy Drug Users by Drug, Frequency of Use, and Gaming Strategy for Selected Drugs During the Past 30 Days

	Frequency of Use (Days during Month)									
	Gaming User					Non-Gaming User				
	1-3	4-10	11-19	20-27	28-30	1-3	4-10	11-19	20-27	28-30
Marijuana	16.20	1.41	2.15	2.35	0.00	1.27	0.00	3.04	0.00	0.00
LSD	4.52	13.57	0.00	0.00	0.00	0.55	0.00	0.00	0.00	0.00
Cocaine	12.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Analgesics	4.17	4.07	1.41	0.00	0.00	18.39	0.00	3.12	0.00	1.43
Inhalants	3.97	1.82	0.00	0.13	0.00	0.60	1.13	2.15	0.00	0.17
Designers	0.00	0.00	0.00	0.00	0.00	0.32	0.00	0.00	0.00	0.00
Any Drug	**40.93**	**20.86**	**3.56**	**2.48**	**0.00**	**21.13**	**1.13**	**8.31**	**0.00**	**1.60**

Using the algorithms discussed in the detection section above, we can estimate the probability of detection during the month and the expected number of months until detection for an inventory of users with this profile. If f_c represents the proportion of users with profile c (frequency and type

(gaming vs. non-gaming)), and $P\left(DET_p^c\right)$ represents the probability of detecting such a user during the month, then the expected probability of detection, $E(P(DET_p))$, can be estimated as:

$$E(P(\hat{DET}_p)) = \sum_c f_c \, P\left(DET_p^c\right) \qquad (15)$$

From (5) the expected time until detection, $E(DET_p)$, can then be estimated as:

$$E(\hat{DET}_p) = \sum_c f_c \left(\frac{1 - P\left(DET_p^c\right)}{P\left(DET_p^c\right)} + .5 \right) \qquad (16)$$

The expected number of drug-days until detection, $E(DAYS_p)$ can be estimated as:

$$E(DA\hat{Y}S_p) = \sum_c f_c \left(\frac{1 - P\left(DET_p^c\right)}{P\left(DET_p^c\right)} + .5 \right) \hat{d}_{w,c} \qquad (17)$$

where $\hat{d}_{w,c}$ represents the estimated number of drug-days per user with profile c.

Such estimates can be obtained from data for specific drugs. A simplified overall estimate can be computed from the frequency of use of any drug data. Using these data from Table 8, the expected probability of detection, number of months until detection, and expected number of drug days were computed for various monthly testing rates.[3] Table 9 presents the probability of detection, the expected number of months until detection, and the expected number of drug-days until detection.

Fitting a quadratic equation through the origin, the following relationship was established $(1 \geq p \geq 0)$:

$$P(\hat{DET}_p) \cong .244p - .0417p^2 \qquad (18)$$

Figure 5 depicts this relationship.

From (16), (17), and (18) estimates of the expected number of months and drug-days until detection can be obtained. These estimates can be used to estimate the detection effects of alternative values of p. Note that the geometric distribution with parameter $(P(\hat{DET}_p))$ can be used to calculate the probability of detection within any number of months. The next section integrates cost-benefits analyses with these methodologies.

[3] Based upon telephone conversations with PNC Flannery, PERS-63, the following average drug wear off patterns (in days) were assumed: marijuana, 2; LSD, 2; cocaine, 3; analgesics, 2; inhalants are typically not tested, but will serve as a proxy for steroids, PCP, barbiturates and other drugs which are tested but for which the positive rate is very small, 2; designers, 2; any drug, 2.

Table 9

Impact of Monthly Test Rate on Detection

Monthly Test Rate (p)	Probability of Detection	Expected Months Until Detection	Expected Drug-days Until Detection
0.00	0.0000	Infinite	Infinite
0.05	0.0123	134.65	600
0.10	0.0242	67.28	300
0.15	0.0360	44.83	200
0.20	0.0474	33.60	150
0.25	0.0587	26.86	120
0.30	0.0697	22.37	100
0.40	0.0910	16.67	75
0.50	0.1115	13.40	60
0.60	0.1312	11.15	50
0.70	0.1502	9.55	43
0.80	0.1684	8.35	38
0.90	0.1859	7.42	33
1.00	0.2029	6.67	30

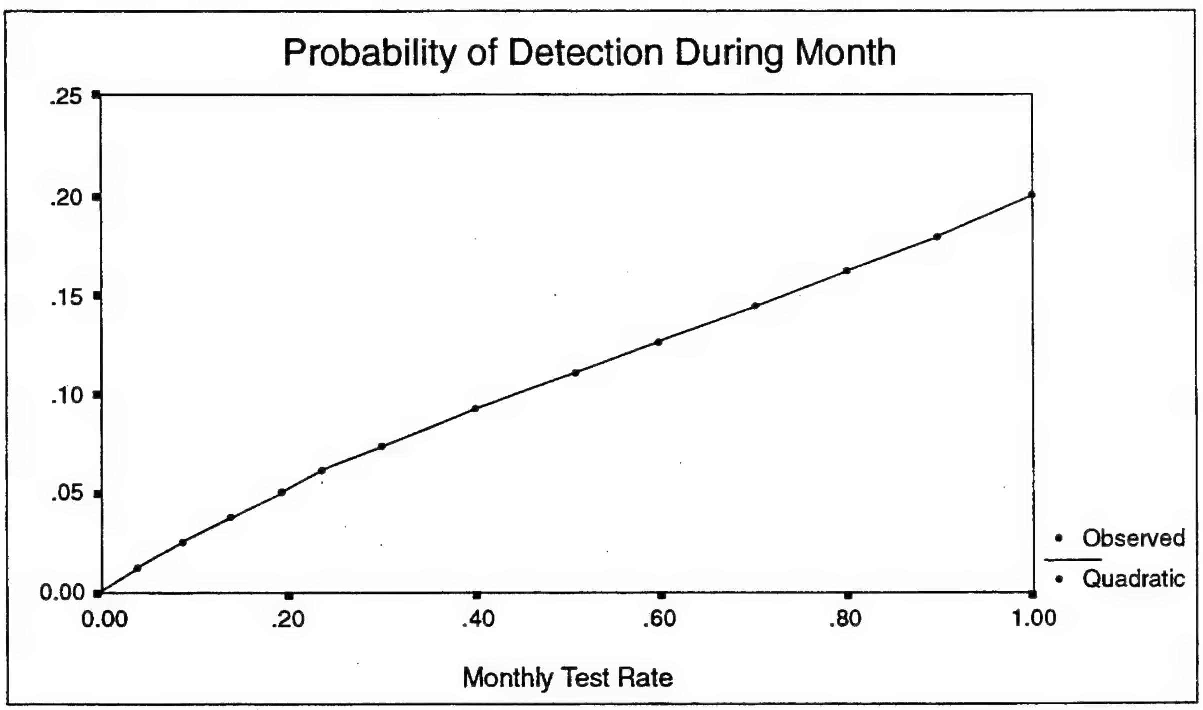

Figure 5. Probability of detection during a month as a function of the monthly test rate.

Results (Cost-Benefit Analysis)

Benefits of Testing

The efficiency criterion in cost-benefit analysis is that projects with positive net benefits should be adopted. In the present case study, although we are examining the optimal scale (test rate) of a project (drug testing) where the scale can be varied over the range of zero to 100 percent testing (or more), the relevant efficiency criterion is the same. In principle, the marginal benefits (*MB*) and marginal costs (*MC*) associated with each different scale should be calculated and the program expanded to the point where $MB = MC$. At this point, total net benefits will be maximized. In the current case study, two main features of the Navy's drug testing program are assumed constant in the analysis: (1) the policy of adopting drug testing over alternatives such as education or prevention programs; and (2) the decision to discharge positive testers rather than referring them to a treatment or rehabilitation program.

In principle, the data generated above permit computation of the marginal benefits associated with the deterrence and detection associated with the drug testing program. However, the current project size (i.e., drug testing rate) is taken as given and compared to a baseline rate of zero testing. Hence, we are comparing the decision to have the program at its present size versus not having the program at all--total benefits versus total costs. If the exercise discovers that total net benefits are positive, it provides strong evidence that the current test rate yields an economic payoff to the Navy. The current rate is not necessarily the <u>efficient</u> testing rate, however, since it is most likely below the point of maximum net benefits. On the other hand, if estimated net benefits are zero or negative, then the test rate clearly exceeds the optimum; but, without clear measures of marginal benefits and costs we cannot identify the exact optimum rate.

One approach to gauging the benefit of reducing drug usage (days) is to use the effect of drugs on employee productivity and to use any observed degradation of productivity as a measure.[4] This benefit would be in terms of costs avoided, a common metric in studies of health and safety programs. Unfortunately, it is difficult to observe the actual degradation in productivity attributable to drug usage. While it is known that heavy alcohol and drug users are more likely to be absent from work, to be late for work, to make errors on the job, to exert less effort in a given task, to make claims for disability or health insurance for medical treatment not related to drugs, and to cause accidents, among other outcomes (McGuire, Ruhm, & Shatkin, 1991; McGuire, & Ruhm, 1993), the exact difference in these problems is difficult to gauge in the absence of controlled experiments. Little information currently exists on the actual differences in these indicators between users and non-users, and when such information is available, it is difficult to link the contribution of the observed difference (such as in errors made on the job or absenteeism) to differences in productivity, and even more difficult to assess the monetary value of that difference to the organization.[5] This problem is especially pronounced when dealing with a service organization, such as the Navy, that does not produce measurable units of physical output but rather intangibles such as "readiness" or "national defense."

[4]It is estimated that the annual productivity loss to U.S. employers from drug abuse alone is $33 billion (Institute of Medicine, 1990).

[5]One study analyzed pre-treatment and post-treatment differences in unauthorized absences, sick days, hospitalizations, NJPs, and accidents for those who completed a drug treatment program (Caliber Associates, 1991).

An indirect measure of productivity differences, however, is available. The indirect approach rests on the conventional assumption in labor economics that workers are paid on the basis of the value of their marginal productivity.[6] Assuming job characteristics and human capital endowments are equal, any differences in pay between two individuals will be determined in large part by differences in their productivity. Therefore, any observed differences in pay for otherwise equal workers, who differ only with respect to their drug use, would provide a measure of how their employers and the labor market as a whole valued the productivity difference between them and their non-drug using counterparts. Numerous studies have estimated the effect of alcohol and drug use on earnings, after controlling for human capital and other factors that also affect pay (Mullahy & Sindelar, 1993; 1994; Kaestner, 1994). Table 10 reviews the estimated pay differentials associated with drug/alcohol use in these studies. They range from approximately zero to a high of .726.

Table 10

Alternative Estimates of Effect of Drug and Alcohol Abuse on Male Wages

		Percent Difference in Wages Associated with Explanatory Variable[a]	
Study	Explanatory Variable	Low Estimate	High Estimate
Harwood, et al. (1984)	Marijuana use	-.279	-.400
French, et al. (1990)[b]	Received treatment	+.06	.16
Register and Williams (1992)	On-the-job marijuana use	-.726	--
Register and Williams (1992)	Long-term marijuana use	-.169	--
Register and Williams (1992)	Cocaine use	0	
	Lifetime cocaine use	-.137	-.224
	New cocaine user	-.225	--
	Past 30-day cocaine use	-.094	-.106
	Lifetime marijuana use	-.079	-.086
Kaestner (1984)	New marijuana use	-.523	--
Mullahy and Sindelar (1993)	Alcoholism	-.188	-.369
Mullahy and Sindelar (1994)	Alcoholism	-.22	-.29

[a]Each study uses a different methodology to obtain the low and high estimates: approaches include using different data sets (e.g., cross sectional vs. panel data), different estimators (e.g., fixed effects vs. simple ordinary least squares), and different model specifications, among others.
[b]French et al. (1990) examine the effect of receiving treatment on the difference between pre- and post-treatment earnings.

The approach of using observed market wages adjusted for other earnings determinants is commonly adopted in cost-benefit analyses of health and safety programs. Observed "compensating wages" for risky jobs have been used to gauge individual workers' willingness to trade-off greater risk (of injury or death) for higher pay. It has allowed researchers to identify the

[6] While there are compensation schemes that deviate from this basic principle of neoclassical theory, this is still the most common approach adopted in empirical work in labor economics (Ehrenberg & Smith, 1994).

monetary value the individual implicitly places on increased workplace safety; that is, how much the individual on average would be willing to pay for a given increase in safety. Worker "willingness-to-pay" is entered as a measure of the economic benefit (i.e., value to the affected group) in cost-benefit studies of safety improvements (Viscusi, 1986; Viscusi & Moore, 1987). In the present case study, market wage differences are used to measure how much employers degrade the pay of drug and alcohol users, and thus as an estimate of the productivity difference between the two groups. This is entered as the economic benefit of programs that reduce or eliminate drug usage.

This approach assumes that a drug user's actual marginal product (*MP*) is positive but is degraded by drug usage. The degradation factor, *d*, acts like a tax on output:

$$MP_a = MP_p(1-d)$$

where MP_a = actual marginal product, and MP_p = perceived marginal product. Since Navy workers are paid on the basis of their perceived marginal product, pay will be based on MP_p, not MP_a. An individual's compensation can be measured as regular military compensation, *RMC*, which includes pay and benefits. Thus;

$$MP_a = RMC(1-d)$$

and it remains to identify *d*, the degradation factor.

Mullahy and Sindelar (1994) point out that prior studies on alcoholism and drug use have concentrated exclusively on the effect of these conditions on one's conditional mean income. They argue that people are typically risk-averse and prefer outcomes that are certain, or at least stable, to those that have greater variability. If a poor health factor, such as alcoholism or drug addiction, increases the variability of income, as well as reduces its mean, then both of these effects tend to reduce an individual's economic welfare.

Their point estimates indicate that alcoholism reduces the conditional mean of income by 22 percent in their data (see Table 10). At the overall unconditional mean of annual income this implies a reduction of $5,152. However, they also estimate the effect of alcoholism on the variance in income, and find a positive relationship. They then include the effects of alcohol use on both the conditional mean and variance of income in computing the certainty (monetary) equivalent of the increased welfare from a (hypothetical) intervention that eliminates alcoholism for an individual. They find this monetary equivalent ranges between $8,400 and $9,900, expressed in 1991 dollars. To obtain the percentage reduction at the mean 1991 income, we use an inflation factor of 47 percent, which represents the growth in nominal weekly earnings between 1980 and 1990 (Economic Report of the President, 1991). This inflates the mean income in their data to $34,427 from $23,420. Using this revised unconditional mean income in 1991 dollars, the monetary equivalent of the effect of eliminating alcoholism in their study rises to between 24 and 29 percent of one's annual income. Conversely, these percentages can be taken to be measures of how much alcoholism degrades productivity (and earnings) in the civilian world. This factor must be multiplied by *RMC* to find the differences in productivity between users and non-users.

A weighted average annual *RMC* for Navy personnel is calculated using the inventories by paygrade for 30 September 1993 and drug usage rates by paygrade (officers and enlisted) reported in Bray et al. (1995); about 95 percent of drug use was in the enlisted paygrades E-1--E-6. The weighted average annual *RMC* for all paygrades was $24,968. Applying the two alternative degradation factors from the alcohol study, the cost to the Navy of the average service member using drugs, and the annual benefit of eliminating such usage, would range between $5,992 and $7,240, or between $24-$29 per day using the average civilian work year.

Using the weighted average *RMC,* the annual benefit of the program is computed as follows. The results from equation (12) indicate, at the current testing rate, a deterrence effect of roughly 60 percent; that is, the usage rate is 60 percent lower than it would be in the absence of testing. Since the use rate would be approximately 10 percent (of Navy personnel) in the absence of testing, then only 4 percent of personnel would use drugs at the current testing rate; thus 6 percent of the personnel inventory would be deterred from using drugs. Applying the inventory figure in Table 3, there are 29,417 fewer users due to the deterrence effect of testing. Applying the two alternative daily cost savings figures, annual benefits from the deterrence effect range from a low of $176.3 million to a high of $213.0 million.

The annual detection rate is about 1.4 percent, or about 6,864 people using the inventory figures in Table 3 above. This figure cannot be counted as the full detection effect because those discharged will be replaced by personnel with some drug usage rate. If the new personnel have a usage rate of 4 percent, then the annual detection effect is 6,864(1-.04) = 6589. The cost avoidance for one year is thus either $5,992 or $7,240 multiplied by the number who are detected and discharged; this yields a low estimate of the annual benefit of detection of $39.5 million and a high estimate of $47.7 million. Combining the deterrence and detection effects, total annual benefits are thus between $215.8 million and $260.7 million.

Note that because the degradation factor is adopted from the experience of the civilian work place, it is likely to understate the potential impact of drug use in the Navy whose personnel often work in ratings or commands where safety is extremely important. Accidents associated with drug use may increase the risk of injury or death to the individual and/or to co-workers, or risk damaging expensive equipment, including aircraft and ships. A single serious accident may impose heavy costs. These consequences will take on added seriousness in a wartime environment. Security concerns are also heightened in a military environment. For many ratings, the degradation factor will likely be much greater than that observed in the average civilian occupation. Only in shore-based ratings that are similar in nature to civilian jobs will the adopted degradation factor be a more accurate representation of the true productivity degradation in the Navy.

Another reason this approach provides a biased estimate of productivity degradation (and benefits) is that the degradation factor derived from the civilian labor market studies is only observed in the labor market for those people who keep their jobs. Market earnings will not be observed at all for those who lose their jobs due to drug use. This group will include those who received treatment or entered a rehabilitation program, but were unsuccessful. The potential market earnings of these individuals will tend to be well below those who use drugs, but who manage to keep their jobs. Thus, a selection bias is present in the labor market studies which tends to understate the true degradation factor in the civilian sector itself.

Finally, program evaluation requires that all relevant costs and benefits be included in the appraisal, including any external or spillover effects. Drug users in the Navy are particularly prone to impose external costs on the organization. This arises in the military environment because production involves teams or units more than individuals. A degradation of an individuals own productivity (or readiness) is likely to further degrade the units readiness. For example, one persons absenteeism may delay deployment of an entire ship, squadron, or weapons system, thus hampering a units ability to fulfill its mission. Similarly, slower repair times on critical equipment may prolong a degraded readiness status for an entire system.[7] In these cases, either the units mission is not achieved, or achievement is delayed, or the drug users external effect must be offset by others. In this regard, drug users are much like on-the-job trainees who not only contribute very little to output, but also require some portion of supervisors and co-workers time to oversee and instruct. The cost of the trainee is the unproductive portion of their own time, plus some portion of supervisors and co-workers time. Thus, the cost of co-workers time needed to offset the lower productivity of the drug user must be included as an external cost.

Thus, on balance, it is highly likely that the civilian degradation factor understates the true degradation associated with drug and alcohol use in the Navy. As a consequence, the benefit calculations above provide downward biased estimates of the true benefits of the drug testing program. If the calculated net benefits of the program are positive using this deliberately conservative factor, we are safe in concluding that the program is economically viable.

An alternative approach can be adopted that imparts an opposite upward bias on the benefit estimates. This is to assume that the true productivity of an undetected drug user is effectively zero. This would be consistent with the zero tolerance policy where detected users are immediately discharged from duty. It is also consistent with the Navy's willingness to bear the replacement costs of the discharged drug users. This approach would adopt a degradation factor of 1.0, so that the detected or deterred drug user's entire *RMC* would be counted as a benefit (cost avoided) rather than a fraction of *RMC*. The economic justification is that the economic damages of an accident due to drug use are so large that even very small positive differentials in the probabilities of such accidents (between users and non-users) produce a very high expected value of damages (expected damages are $E(D) = p(D)$, where p = the differential in the probability of an accident that imposes damage costs of D. If, for example $p = .05$, but D = \$10 million; $E(D)$ is \$500,000.

If we recalculate the benefits under this approach using, total benefits jump to \$899.0 million. This is composed of an annual deterrence effect of \$734.5 million plus a detection effect of \$164.5 million.

[7]It might be argued that the civilian degradation factor already accounts for this external cost because civilian firms would be able to internalize the effect within their own organization. This would be true only if civilian firms relied on team production as extensively as the Navy. The extreme case would be if civilian firms paid only on a piece-work (individual) basis and organized no production in teams, whereas in the Navy all output would be produced by teams. The true situation lies somewhere in between this and other extreme cases, but our judgment is that the proportion of output produced by teams/units in the Navy is much higher than in the civilian world.

Program Costs

Program costs include the laboratory costs for the drug testing, the lost productivity associated with taking the tests, and the cost of replacing discharged personnel who test positive. The program costs for fiscal year 1995 were $20.6 million for Navy testing only.[8]

The lost productivity of employees taking the test can be calculated as follows. The average employee is tested 2.4 times per year. We assume that the test itself takes only 10 minutes to complete. Nonetheless, multiplying the inventory figures in Table 3 by 2.4 and multiplying again by 10 minutes yields a productivity loss of 196,000 hours each year. Using the average *RMC*, and an average hourly wage of $12, this yields a dollar value of the lost productivity of $2.4 million.

Accurate estimates of replacement costs require information on the paygrade, length of service, and rating of the discharged individuals. Replacement cost tables are available from the Navy for each of these dimensions. An approximation, however, can be made by estimating the replacement cost of the average individual. We follow the same approach as used when estimating average weighted *RMC*, again using the drug usage rates by paygrade from Bray et al. (1995). We then apply the median years of service for each paygrade group and apply this to the yeoman (YN) rating to obtain replacement cost for detected drug users. The YN rating has a fairly low replacement cost due to a short training pipeline and high continuation rates. We adopt it here as a reasonable first approximation, in part because screening by the Navy and self-selection by applicants may prevent those prone to drug use from entering highly technical ratings with long training pipelines. Using these assumptions, the replacement cost for the 6,864 discharged positive testers would be $214.7 million. When added to annual program costs of $20.6 million and lost time of test takers of $2.4 million, the total cost is $237.7 million.

If we use the "high estimate" of benefits using the partial degradation factor (.29) we obtain positive net benefits of approximately $23 million. If we use the full degradation factor (1.0) we obtain positive net benefits of $661.3 million. Note that we stressed that the civilian, partial degradation factor definitely understates the true degradation in the Navy environment where workers operate very expensive equipment and accidents are extremely costly. The key issue is the following: How much higher is the true Navy degradation factor? While the true degradation factor is not 1.0, it is far safer to err in the direction of 1.0 than in the direction of .29. The program generates net positive annual benefits using an implausibly low factor of .25, and our judgment is that the true Navy degradation factor exceeds the "high" factor of .29. Thus, the cost-benefit analysis clearly indicates that the current testing rate is economically justifiable.

Conclusions and Recommendations

The preceding sections developed a conceptual model for determining an optimal drug testing policy. The model outlined methodologies for estimating the detection and deterrence effects of alternative drug testing rates as well as the costs and benefits of alternative policies. Various techniques for measuring drug use were discussed including the proportion of individuals who used drugs at least once during a period (e.g., month, year) and the number of accumulated drug

[8]Correspondence from PNC Flannery, PERS-63.

days. Estimated civilian and Navy drug use were compared in order to estimate the benefits of drug testing. Preliminary estimates derived from the conceptual model indicate that present levels of testing (approximately 20% per month) are cost beneficial. Testing at present levels is estimated to yield annual net benefits of at least approximately $23 million. It is recommended that the conceptual model form the basis of a computerized drug policy analysis system for use by drug policy managers to determine optimal drug testing strategies. It is further recommended that additional parameters such as differential testing for specific drugs (i.e., pulsing) and a wider variety of drug testing strategies (e.g., testing based on anticipated likelihood of drug use) be incorporated into the model.

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Appendix A

Values of $\hat{d}_{w,k}$ for w = 2

Table A-1

Values of $\hat{d}_{w,k}$ for w = 2

	Strategy	
Frequency (k)	Non-Gaming	Gaming
2	3.9	3.0
7	12.6	8.0
15	22.8	16.0
24	29.0	25.0
29	30.0	30.0
Overall Average:	8.29	

Distribution List

Chief of Naval Personnel (PERS-00), (PERS-00B), (PERS-00W), (PERS-00H), (PERS-6), (PERS-6C), (PERS-6E), (PERS-63), (PERS-63E),
Chief, Bureau of Medicine and Surgery, Washington, D.C. (MED-244)
ODASD, Drug Enforcement Plans and Support
Office of Naval Research (Code 34), (Code 342)
OCDEP&S, Science and Testing Programs Officer
Armstrong Laboratory, Operations and Support Directorate(AL/DO), Brooks AFB, TX
AL/HR-DOKL Technical Library, Brooks AFB, TX
Chief of Naval Operations (N091), (N813)
Deputy Assistant Secretary of the Navy (Manpower and Reserve Affairs)
Director of Research, U.S. Naval Academy
Office of the Assistant Secretary of Defense (P&R)
President, Naval War College (Code E-1121)
Superintendent, Naval Postgraduate School
Defense Technical Information (DTIC) (4)